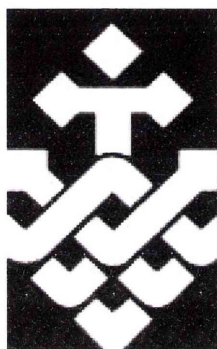


# A Directed Learning-based Evolutionary Approach for Legged Robot Motion

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A Thesis submitted for the degree of Master of Science  
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MSc

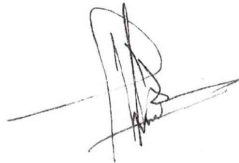
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I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

**Signature of Student**

A handwritten signature in black ink, consisting of a stylized 'B' with a horizontal line extending to the left and a diagonal line extending to the right.

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**Sydney, Australia,**

**Muhammad Anshar**

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## Abstract

At any stage of development, any organism is required to go through a learning phase as a way to acquire and enhance certain skills. Similarly, legged robots perform a learning phase to obtain basic skills before implementing them in real specific applications. Walking skills are one of the first capabilities that need to be learned, as this allows the robots to traverse their environment.

This thesis will focus on the learning to walk task for legged robots using machine learning techniques. This task is aimed to develop *framed optimal* walking gaits which typically concern the *speed* and *stability*. In brief, the *framed optimal* walking gaits are obtained from a particular region in the search space which is framed within the previous robot learning experience or history.

We found that the long deployment of the robot at the learning stage which utilises machine learning techniques will eventually raise the significant impact of *wear and tear* and it is undesirable for robots to be worn out just to perform the learning task before they are deployed in. Typically ML techniques require thousands of trials to find globally optimal solutions, however, this is not an option for robot learn to walk approached since an average robot would be unable to complete the trials intact. In relation to this issue, we propose a Directed Evolutionary Algorithm Learning method – which we henceforth refer to as the *DEAL* method. This method aims to direct the learning process by incorporating the robot learning experience, and hence, to reduce the time period required for the learning process to converge to a *framed optimal* solution. This will reduce the deployment time of the robot and as a result, the learning process will have a minimal impact on the *wear and tear* of the robot body and maximise the life of the robot when it is deployed on specific applications.

We empirically conducted literature studies on the four-legged AIBO robot which is a benchmark platform for the international robot soccer competition, RoboCup,

and ran the experiment within the same robot platform. The results of the implementation of the *DEAL* method show that the learning lasts for shorter time than the previous methods used by the University's RoboCup Robot Soccer Team, *UTS Unleashed!* and as a result, in the long term, the robot productivity will increase through the enhancement of its lifespan and thus its ability to perform other tasks.

The objectives of future work will also address the significant factor of *wear and tear* at any time during robot deployment. The benchmark of the experiment of the *DEAL* method and associated experimental design will also be expanded to the humanoid robots, the BIOLOID and the NAO robots.